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THE ROLE OF LENDERS' GEOGRAPHICAL DIVERSIFICATION IN P2P TRANSACTIONS

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Abstract:

In this dissertation, I provide novel evidence of the impact of geographical diversification on loan interest rates. The findings, based on a unique dataset of all P2P transactions in a UK platform over the period 2010-2013, suggest that more geographically-diversified lenders are more likely to impose lower interest rates in their contract terms in P2P transactions, while more concentrated lenders (in terms of geographical concentration of the activities) practice higher loan interests rate. These results are robust to an alternative econometric approach.

Keywords:

Peer-to-peer credit markets, screening, geographical diversification, diversification

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Preface/Intro

Peer to peer (P2P) lending is a loan modality mostly targeting individuals and small/medium enterprises (Sciarrone-Alibrandi et al., 2019). It represents an alternative solution to the traditional banking channel, and it is also an appealing source of investment diversification.

The development of digital technology, commonly known as “fintech”, is increasingly involving the financial sector. New organizational structures along with the search of new distribution channels and the increasing digitalization, aimed at containing operating costs and maximizing revenues, have encouraged the institutional operators to seek new ways of creditworthiness. The advancement of the fintech credit has increased the number of operators offering financial services and brought a broader range of products, offered in addition to traditional services, which used to be the exclusive preserve of banks. Companies in the Fintech world provide many consumers with access to a wider range of payment, investment, advisory and financing services.

As in Claessens et al. (2018): “Fintech credit offers an alternative funding source for businesses and consumers and may improve access to credit for underserved segments”. As it is well known, this category of borrowers usually receives less attention from large financial institutions due to the excessive fragmentation of applicants and due to the difficulties in assessing creditworthiness. Later we will see in depth how the latest credit crunch and the low rates of return, resulting from the 2008 subprime (high risk) mortgage crisis, have led investors to look for alternative forms of investment.

The social lending sector has taken shape by exploiting the opportunities offered by technological innovation.

The market landscape that we are experiencing and that we will presumably continue to deal with is, as it has already been mentioned, characterized by extremely low interest rates on loans and deposits. This is a condition in which it is virtually impossible to find room for significant intermediation costs. The dynamics of interest margins, particularly in relation to the capital requirements for intermediaries, suggest that it is difficult to narrow the gap between mark-up and mark-down. In this logic, the meeting of the demands of investors who aspire to higher yields and borrowers who want lower rates pushes even more towards disintermediation, and therefore towards the growth of the Peer to Peer (hereafter, P2P) lending phenomenon.

The purpose of this work is to demonstrate how geographical diversification significantly affects the rates applied to this type of loans.

The study is structured as follows. Chapter 1 introduces the definition and the mechanism of the P2P. Chapter 2 analyses the extant literature on the P2P lending, while Chapter 3 delves into the statistical analysis of this dissertation.

CHAPTER 1: An introduction to peer-to-peer lending

1. Introduction

Peer to peer lending, also known as social lending or P2P is nothing more than a loan between private individuals through the use of online platforms and not through the traditional channels (Sciarrone-Alibrandi et al., 2019). In essence, P2P allows a lender to transfer money to one or more applicants through an online platform at competitive interest rates (De Luca-Lucido, 2020). The applicant (borrower) can be a private person (P2P) or a company (P2B); in the latter case, the literature refers to Peer to Business.

P2P is part of alternative finance and draws its origins from a specific area of crowdfunding known as lending-based crowdfunding. The increased interest in such a crowdfunding phenomenon has been one of the main consequences of the dramatic events following the 2008 crisis that affected the entire financial industry. In fact, generalized distresses in the banking sector and the real economy have established a lack of confidence in the typical role of financial intermediaries in bridging surplus and deficit agents (namely disintermediation) and directing funds in the real economy. This climate has boosted the demand for alternative forms of finance. Nowadays, peer-to-peer lending is a valid alternative channel of access to credit via the web by overturning the usual paradigm.

2. The P2P mechanism

In principle, the P2P lending requires the interaction of two agents: i) the applicant, and ii) the investor. On the one hand, an individual agent (both a person or, in some specific circumstance, a firm) applies to register on a P2P loan platform, and, once registered, he/she/it publishes an announcement about the amount needed in the P2P platform by assuming the role of applicant.

On the other hand, all the platform members who are willing to channel their money to the potential borrowers by assessing their requests are called lenders.

Of course, the entire process is not devoid of security checks. First, the borrowers must ensure that the details provided are reliable. These details include checks on the release of real personal information, such as date of birth, chambers of commerce membership, bank account, social security number (Zopa, 2020). This information is then compared with that one contained in the databases of tax collection agencies and bodies engaged in the fight against tax fraud and money laundering.

Once the identity is verified, the second check entries into force, namely the evaluation of the borrower's economic capacity. This phase is based on the consultation of various public and private databases and results in a credit score, which measures the degree of reliability that an entity has in fulfilling its commitments.

Furthermore, the platform internally calculates a predictive rating that shows the probability of insolvency. Based on this score, the applicant is classified in a particular risk category.

Finally, the requirements for P2P borrowers vary across countries and platforms. Common requirements are usually related to the residence in the countries served by the platform, the amount, and the duration of funding required.

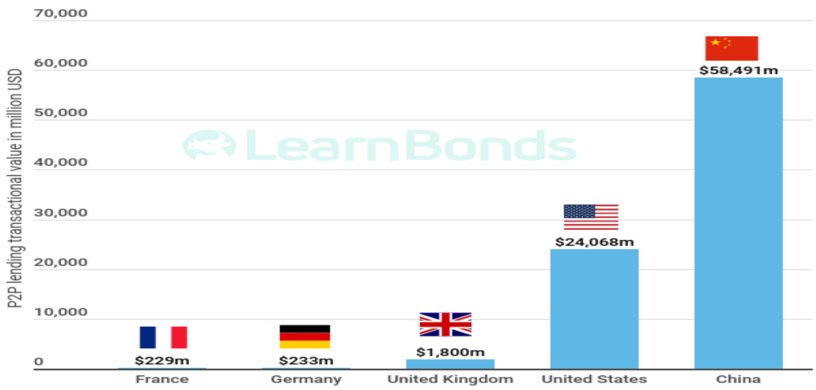
3. P2P numbers at a glance

2019 was an important year for the p2p transactions. Considering only the top-market, the cumulated amount of operations accounted for US $86.33m. The first-ranked market in the world is China with a total amount of transaction of $58,491m, followed by the US with $24,068m, the UK with $1,900m followed by other countries such as France and Germany with lower volumes (Baltrusaitis,2020).

According to the forecasts of Baltrusaitis (2020), the P2P business might increase its rilevance in comparison with other segments of the financial markets by reaching the threshold of $460 billion of annual production in 2023. Analysts agree to represent a production scenario characterized by a CAGR estimated at over 50% per year.

Figure no. (1) clearly shows the volumes stipulated at the end of 2019 for the countries where this phenomenon is most developed.

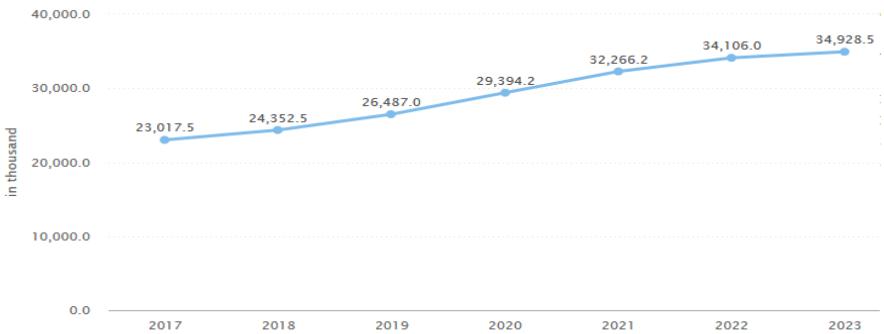
Fig. 1 Annual production P2P major countries.



Source: Statista 2019

According to the same study, the amount of successfully financed loans was 26.5 million in 2019 and will reach 34.9 million in 2023. This increase is not negligible since it represents an increase of 31% over the four-year period.

Fig. 2 Number of financed loans worldwide



Source: Statista 2019

CHAPTER 2: Literature review

1. Introduction

In this section, I provide a review of the literature upon the peer-to-peer lending market. It is essential to point out that most papers extract data from Prosper.com, one of the two leading Us peer-to-peer lending platforms, which allows researchers to access data about listing loans and information about borrowers and lenders.

Ideally, the review of the literature may be divided into two parts. Firstly, I analyze previous papers on the main characteristics of peer-to-peer lending conditions, such as interest rates, default probability, and loan success. Secondly, I review papers on the role played by social intermediation and group leaders in affecting interest rates and loan success.

2. P2P Success determinants

Researchers provide evidence that a series of factors consistently affect lending conditions in online peer-to-peer lending platforms. According to Bachmann and Becker (2011), interest rates vary by the type of Peer-to-peer lending platform. While in the commercial platforms, investors gain profits from the risk they undertake, loans in non-commercial platforms appear to be viewed as "donations," whose aim is to fund projects in underdeveloped countries in the world. For this reason, interest rates in the non-commercial platforms are extremely low or even zero.

Since commercial platforms employ different procedures to match the demand and supply side, Wei and Lin (2017) investigate the impact that different market mechanisms have on lending and interest rates paid by borrowers. In their paper, these mechanisms are auctions and posted prices, respectively. On the one hand, Wei and Lin (2017) suggest that auctions provide borrowers with better conditions in terms of interest rates, even though the funding probability is, on average, 30 percent lower than under posted price-mechanism. On the other hand, they suggest that loans funded under the posted-price regime are less likely to be repaid. Mainly, the switch from auctions to posted price mechanisms has led to a higher cost of debt for borrowers, a higher probability of lending success, and a higher credit risk for lenders.

The role of disclosure in mitigating information asymmetry and reducing market inefficiencies has always been a central subject of extensive research. A bunch of researchers has focused on disclosure in peer-to-peer lending because these platforms allow borrowers to provide unverifiable and voluntary information (such as contract terms of other debts, explanations for low credit ratings, a description of the loan purpose, family status or a personal picture). Among others, Michels (2012) demonstrates that the more is the amount of voluntary disclosures provided by the borrower, the less is the interest rate on loan. Indeed, additional voluntary disclosure is associated with a 1.27 percent reduction in the interest rate and an 8 percent increase in bidding activity. Hence, voluntary and unverifiable disclosures seem to be a strategic tool for borrowers to promote their listings more efficiently and increase their trustworthiness. In Iyer et al. (2016), soft information is related to the ability of lenders to evaluate borrowers' credit quality. In this study, the authors suggest that lenders in Prosper.com market appear to be extremely able to screen borrowers and that soft or nonstandard information is relatively a better indicator when screening less creditworthy borrowers. In addition, Iyer et al. (2009) find that, in each credit category, borrowers at the top of the category are on average funded at 140-basis-points lower rate compared to the borrowers at the bottom of that category. This finding constitutes a further demonstration of the ability of lenders to evaluate borrowers' creditworthiness. Herzenstein et al. (2011) find that unverifiable information increases the probability of funding and reduces loan interest rates. Still, it cannot be considered as a good predictor of the borrower's creditworthiness. Conversely, this study finds that a higher amount of voluntary information is associated with a lower probability of loan repayment.

One of the central research questions is whether loan fundability in the peer-to-peer lending market is related to some personal characteristics of loan applicants coming from the attached picture, such as race, age, and gender. Pope and Sydnor (2011) find that the characteristics displayed by borrowers through their pictures strongly affect their access to credit. Particularly, in the Prosper market, loan listings with pictures showing black people are 3.2 percent less likely to be funded, which represents approximately one-third of the total funding probability of the platform, which represents 9.3 percent. In comparison with listings of white applicants with similar credit profiles, black applicants are 25 to 35 percent less likely to have their loans funded. Also, black borrowers pay a 60-basis-points higher interest rate than white applicants do with similar credit profiles. Surprisingly, the higher interest rates paid by black borrowers are not high enough to compensate for their higher default probability. This finding is also supported in Emekter et al. (2014), who analyze the Lending Club market, an alternative platform of the Prosper.com. Finally, Pope and Sydnor (2011) find that older and overweight applicants pay considerably higher interest rates, whereas women and people signaling military involvement pay significantly lower interest rates.

Ravina et al. (2008) confirm the existence of significant racial disparities in the peer-to-peer market. In her study, she finds that black borrowers pay between 139 and 146 basis points more than white borrowers. In contrast to Pope and Sydnor (2011), gender and age do not seem to affect the interest rate significantly, and there is no evidence of a higher probability of delinquency by black applicants. Interestingly, Ravina et al. (2008) stress the role of appearance shown by applicants through their profile picture in leading lenders' investment decisions. In other words, she finds that borrowers whose appearance is rated above average are more 1.41 percent more likely to have their loans funded and pay 81 basis points less than an average-looking borrower with the same socioeconomic characteristics. However, "beautiful" borrowers are found to have a greater tendency to delinquency.

Appearance is also a central subject in Duarte et al. (2012). They confirm that borrowers who are perceived to be less trustworthy have more difficulty getting funded, strengthening the idea that lenders rely much on applicants' physical aspects when deciding to fund a loan listing. In quantitative terms, in the case of the trustworthy borrower, bidding activity is 31 percent more intense than the average auction. Additionally, a borrower who appears trustworthy can promise an interest rate 105 basis points lower than a borrower who appears less trustworthy with the same funding probability. These findings are consistent with Emekter et al. (2014), who suggest that borrowers with high FICO scores, high credit grades, low revolving line utilization, and low debt-to-income ratio are associated with low default risk. The same authors also find that default probability increases as the duration of loans increases.

In contrast to Duarte et al. (2012), Gonzalez and Loureiro (2014) find that borrowers do not take advantage of attractiveness, but instead of age. Lenders tend to deem older borrowers more trustable because they are considered as more experienced and skilled. This might explain why this category of borrowers receives a more significant fraction of loans.

In the spirit of Klafft (2008), credit rating is the most crucial factor affecting the interest rates, and the debt-to-income ratio takes the second place. Besides this fact, he also suggests that borrowers owning a bank account or members of online peer groups are more likely to have their loans successfully processed. Similarly, Iyer et al. (2009) confirm that lenders typically base most of their inferences on the borrower's creditworthiness from hard, factual information mentioned by Klafft (2008).

Thus far, previous papers refer to the US peer-to-peer lending market. From a different premise, Feng et al. (2015) study the role played by information in the Chinese market. In contrast with the US case, China is a peculiar setting because official credit information on individual borrowers is often unavailable. This circumstance implies that lenders rely much on information provided by the applicants to assess their creditworthiness. Furthermore, they also find that the effect of gender has an impact only on funding success, and there is no evidence that women benefit from lower interest rates. Concerning age, the authors agree with Gonzalez and Loureiro (2014) that lenders prefer older borrowers, who, in turn, are capable of proposing and receiving loans at better conditions.

Interestingly, Barasinska and Schäfer (2014) analyze data extracted from the leading German Peer-to-peer lending platform, *Smava*. She finds that in the German market, there is no effect of gender on lending decisions. Thus, in contrast with Pope and Sydnor (2011) and Ravina et al. (2008), focusing on the US market, there is no evidence of gender discrimination in this market accordingly.

3. Group intermediation

An essential feature of the online peer-to-peer lending platforms is the possibility for borrowers and lenders to join in groups in which members share common characteristics such as employment, geography, education, everyday leisure activities. Many researchers have investigated the effect of group intermediation on funding conditions.

Herrero Lopez (2009) shows that memberships to some key-groups play a central role in facilitating access to credit. Membership represents a sign of higher trustworthiness by lenders participating in the online peer-to-peer lending market. They also show that the affiliations with trusted groups double the probability of getting a loan listing wholly funded and allows borrowers to have more reasonable interest rates. In addition to previous studies mentioned above, they also find that unattractive features susceptible to undermining the success of a listing may be worked out by other tools provided by social intermediation. Two examples of these tools are affiliation to highly rated groups and feedback about previous transactions. Berger and Gleisner (2009) suggest that groups provide better funding conditions because borrowers within groups tend to act more diligently towards each other. Mainly, they emphasize the role of the group leader as a financial intermediary between lenders and borrowers. According to their findings, the group leader bidding is considered by the market as a strongly credible signal for the creditworthiness of other members because is a strategic tool employed by group leaders to promote members' listings. Hence, it enables lending at better conditions.

Although Greiner and Wang (2009) agree that social intermediation is a critical factor for credit access in terms of interest rates, they also demonstrate that social capital is not a good predictor of the loan payment. In other words, it entails that its incapability of helping lenders incorrectly allocate their financial resources.

There are mixed pieces of evidence on the relationship between group size and interest rates. On the one hand, Berger and Gleisner (2009) and Collier and Hampshire (2010) find that a larger group size leads to lower credit spreads due to more effective peer-monitoring. On the other hand, Freedman and Jin (2017) posit that loans from smaller groups have lower default rates.

Collier and Hampshire (2010) hypothesize that the behaviors adopted by group members may be a strong signal of trustworthiness to the market and somehow influence the lender perception of borrower credibility. Specifically, they distinguish between *behavioral community signals*, which refer to actions taken to enhance the borrower trustworthiness, such as placing bids on the borrower loan, and *structural community signals*, which consist in the structural features of the community and not in the intervention of the members, for instance, the community size. The researchers show that both structural and behavioral signals act as signals of credit quality and may lower the cost of debt for borrowers. Similarly, Lin et al. (2013) confirm that social connections in online Peer-to-peer lending can increase the probability of successful funding and provide borrowers with lower interest rates. In other words, according to this study, social networks turn out to be misleading for lenders, who tend to rely on this aspect to assess borrower trustworthiness.

In contrast to the mentioned studies, other researchers have expressed a more critical opinion about social connections in the peer-to-peer lending market. Hildebrand et al. (2017) criticize group leader bids, which may be used strategically to enhance borrower credibility, especially when group leaders benefit from fees in case of success of a member listing loan. Such bids may also be used to encourage the listings with high credit risk and subsequently may mislead lender decisions. In fact, according to this study, group leader bids result in lower interest rates, but, at the same time, show higher default rates as well. These considerations are partially agreed by Freedman and Jin (2017), which confirm that social ties in Peer-to-peer lending do not always reflect the borrower risk of default.

4. Geographical diversification

Geographical diversification has been one of the most central themes in financial economics and management literature. Making use of the Abell framework (1979), geographic diversification refers to the situation such that an economic agent satisfies the needs of the same segments of customers, by employing a similar technology, but offering to different country-customer groups. In the last years, this tendency to diversification has become an essential strategy for firms and agents to create value, gain a competitive advantage, and, especially, access to new opportunities and competences.

However, this trend is also reflected in the financial services sector, where the saturation of the local and national markets is not negligible by posing new challenges for financial agents. Indeed, the geographical diversification can be considered an evolutionary process is driven by either rational reasons of the agent or opportunistic behaviours (among others, herding between peers).

However, there is no evidence in the peer-to-peer lending literature about the effects of geographic diversification on loan interest rates. For this reason, I borrow some hints from management, economics, and banking literature. For instance, the management literature posits that such operational expansion, if successful, allows firms to strengthen corporate skills, improve the management of the supplying process, and to spread new knowledge through the accumulation and the valorization of tangible and intangible resources (Sicca, 2003).

The financial economics literature underlines that the diversification is beneficial because it leads to a positive risk-adjusted return on the capital invested (Clarke 1985 and Teece 1982). This appears to be consistent and coherent with the Markowitz mean-variance models. According to this strand of the literature, geographical diversification is justified whether the investment shows a correlation equal to zero (or better negative correlation) with the other investments in the portfolio. Conversely, the microeconomic theory postulates that the diversification is advantageous only if it allows the firm to achieve synergies and share resources to benefit from scale economies. To exploit synergies, the diversification requires a certain level of correlation across different activities and similarities. In turn, it entails that the foreign activity is exposed to considerably correlated risks, for instance, political-institutional risks.

Finally, the banking literature delves into the role of geographical diversification on bank's efficiency. Among others, Deng and Elyasiani (2008) analyze the relationship between geographic diversification and firm value in the US banking market, suggesting that revenues coming from economies of scale and synergy overcome the agency costs produced by the diversification strategy. Also, the authors find that a bank holding company that is more geographically diversified shows more stable prices. Conversely, Gulamhussen et al. (2012) show that geographical diversification is associated with an increase in the level of risks.

CHAPTER 3: Empirical analysis

1. Introduction

In this section, I provide a novel evidence on the impact of geographical diversification on the interest rates charged on loans by lenders in online peer-to-peer lending market. Specifically, the investigation aims at providing an original contribution to the existing academic literature about peer-to-peer lending by investigating whether lender's geographical diversification has an influence on loan interest rates in the online peer-to-peer lending market. For this reason, I test these two following alternative hypotheses:

H0: *The geographical diversification does not affect the loan interest rates.*

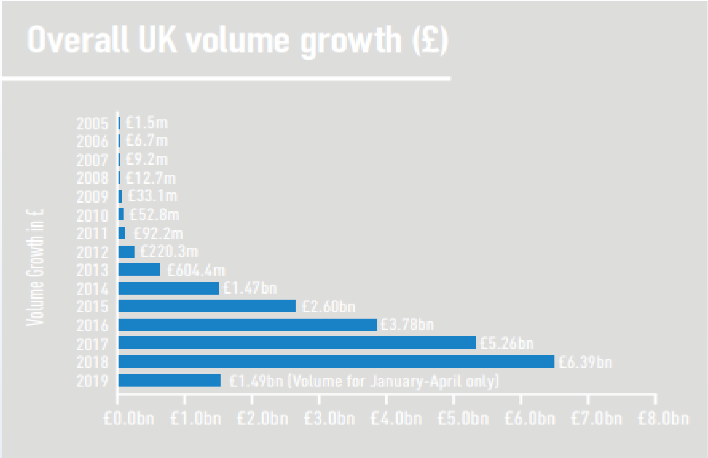
H1: *The geographical diversification negatively affects the loan interest rates.*

The rest of this chapter is structured as follows. In the first part of this chapter, I provide a complete description of all the variables included in the regression models. Second, I report descriptive statistics for the main variables used in this following analysis. Finally, I present the empirical results and robustness tests.

2. Data and sources

This work is based on UK regional market data because the British market is one of the most developed online peer-to-peer lending markets in the world. Indeed, the UK market was the first country to adopt this specificity of loans, confirming year after year its position as the European leader (transaction volumes around £17.2 billion). Currently, there are currently 15 operating platforms. In this study, I use as a primary source of data the database of Open Data Institute, a leading UK platform for the P2P lending.

Fig. 3 Overall UK volume growth 2005-2019



Source: ALTFI.com

More specifically, the dataset used in this study is characterized by 882,610 observations extracted from Open Data Institute (hereafter ODI), concerning loans provided by lenders in online peer-to-peer lending market between 2011 and 2013. Particularly, the dataset includes information on lender origin, borrower origin, origination date, maturity date, terms and loan rate. Therefore, I hand-build the different geographic measures of this study based on the information in the ODI dataset.

Since the study focuses on geographical diversification, all the observations have been divided by geographical areas, based on the provenance of lenders and borrowers. Precisely, for the purpose of this study, UK territory is divided into 12 areas according with the guidelines provided by Open Data Institute: East of England, South East, South West, North East, North West, London, Yorkshire, The Humber, East Midlands, West Midlands, Wales, Scotland, Northern Ireland.

3. Dependent variables and Independent Variables

In this section, I describe all the variables used in the univariate and multivariate tests.

Since this scope of this study is to evaluate the effect of the geographical diversification of lenders on the loan rate, of course, the main dependent variable is the interest rate charged by lenders on loans (*Loan Rate*).

I use different proxies for geographical diversification. First, I use *Same Region* dummy, which takes the value of 1 if the lender and the borrower are from the same region. Second, I use as an alternative measure of geographical diversification, the number of regions in which the lender provides funds on the platform scaled by the maximum number of regions in which the same lender might operate in the platform (*Geo Diversification*). Since the Open Data Institute divides the UK in 12 regions, I assume that the denominator of this ratio has a maximum value of 12. Third, I use also a measure of operational concentration of the lender, namely, the proportion of the lender's transaction per region, which is calculated as the ratio between the number of loans provided by a lender in a single region and the total number of loans provided by the same lender (*Fraction Area*). Finally, I also use a measure of dispersion, which is the standard deviation of the *Fraction Area*, namely *Geo Volatility*.

Last but not least, I also use a set of controls loan-specific, region-specific, and borrower-specific to allow for the incidence of the potential omitted variables in my estimates. Particularly, I use as a control the log of the loan term. This is consistent with the idea that a higher duration corresponds to higher interest rates. Then, I use a series of region-fixed effects (of the borrower and of the lender) to account for observable and unobservable regional factors that may explain the variation of the dependent variable (*Loan Rate*). I also include the log of total amount lent by a single lender to any P2P borrower.

This is also coherent with the theoretical prediction that regional factors of the demand-side and the supply-side may affect the decision of undertaking a geographical diversification strategy (Sicca, 2003). Finally, I also account for the loan origination year fixed effects to account for the fact that the origination year of loans may affect the levels of interest rates and loan terms.

4. Methodology

I implement a OLS regression analysis in which the interest rates charged by the lender in each transaction is regressed on the following variables: the geographical diversification, the loan term, and a bunch of region-fixed effects, borrower fixed-effects, and loan origination year fixed-effects.

The OLS regression model is described by the following statistical specification:

$$\textit{Loan Rate}_{i,j,t} = \alpha + \beta \textit{ Geographical Diversification}_{i,t} + \gamma \textit{ Controls}_{i,j,t} + \varepsilon_{i,j,t} \quad (1)$$

where *Loan Rate*$_{i,j,t}$ is the interest rates charged by the lender i to the borrower j at time t; *Geographical Diversification*$_{i,t}$ is the proxy chosen for degree of geographical diversification of the lender j, and *Controls* include a vector of controls aforementioned.

In some robustness tests, we also rely on Robust Regression (Li, 2011) in order to mitigate that my results are driven by the presence of potential outliers.

5. Summary statistics

Table 1 shows the main summary statistics of the variables included in the analysis. The average interest rate charged on loans of the sample is 6.87 per cent. In general, lenders show a significant tendency to provide loans outside of the regions they come from, as shown by the mean of *Same Region*. On average, the proportion of transactions per region, represented by the variable *Fraction Area*, is 9.44 per cent, while the mean of *Term (ln)* is 3.6814.

Table 1
Summary statistics

VARIABLES	(1) N	(2) Mean	(3) Median	(4) SD
Interest Rate	882,610	0.0687	0.0658	0.0120
Same Region	882,610	0.0957	0.0000	0.2942
Geo Diversification	882,610	0.9992	1.0000	0.0372
Fraction Area	882,610	0.0944	0.0952	0.0270
Geo Volatility	882,610	0.0269	0.0265	0.0023
Term (ln)	882,610	3.6814	3.5835	0.3111
Size (ln)	882,610	2.6982	2.3026	0.7219

In fact, Table 2 shows that, from 2010 to 2013, on average, interest rates charged on online peer-to-peer loans significantly decrease by 1.78 per cent. Furthermore, loan terms predictably decrease as well. Moreover, this evidence provides some hints that higher terms (defined in terms of timespan) of the contract is associated to higher interest rates

Table 2
Average of the variables by origination year

Origination year	(1) Interest Rate	(2) Term (ln)
2010	0.0805	3.7149
2011	0.0718	3.7039
2012	0.0703	3.6824
2013	0.0627	3.6594

Table 3 reports the correlation matrix of the main variables included in the regression models. In general, there are no remarkable correlations coefficients among the variables. This is also important for potential problems of multicollinearity in our specification models. The only coefficient which is statistically significant is again the correlation between *Interest Rate* and *Term (ln)*, which is equal to 0.438, at 1 per cent significance level. This result confirms the view that higher loan terms are associated with higher interest rates, because long-term loans are considered riskier by the investors, that, in this specific exercise are the lenders. Interestingly, I also observe a positive correlation between the amount lent by the lender to any borrower and the interest rate. This is line with the common view that higher amount lent by the lender is associated to an increase in the level of interest rates (Mishkin, 2018).

Table 3
Correlation matrix

	Loan Rate	*Same Region*	*Geo Diversification*	*Fraction Area*	*Geo Volatility*	*Size (ln)*	*Term (ln)*
Loan Rate	1.0000						
Same Region	0.0003 (0.7786)	1.0000					
Geo Diversification	-0.0262 (0.0000)	0.0004 (0.7215)	1.0000				
Fraction Area	0.0179 (0.0000)	0.0655 (0.0000)	-0.0364 (0.0000)	1.0000			
Geo Volatility	0.0607 (0.0000)	-0.0024 (0.0256)	-0.3225 (0.0000)	0.0527 (0.0000)	1.0000		
Size (ln)	0.1538 (0.0000)	0.0021 (0.0485)	-0.0137 (0.0000)	0.0154 (0.0000)	0.0117 (0.0000)	1.0000	
Term (ln)	0.4376 (0.0000)	0.0014 (0.1970)	-0.0009 (0.3924)	-0.0089 (0.0000)	-0.0115 (0.0000)	-0.0197 (0.0000)	1.0000

In parentheses, the p-values of the correlation matrix are reported

6. Empirical results

Table 4 shows the empirical results of OLS regressions. As mentioned, I include region-fixed effects both for lenders and borrowers and origination year fixed effects to control for time of loan origination. In each column of Table 4 we use different measure of geographical diversification.

Column (1) uses as measure of geographical diversification *Same Region*, which is weakly significant at 10% and is positively correlated with the *Interest Rate* suggesting that undiversified lenders impose higher interest rates. Interestingly, Column (2) shows a negative relation between the number of the regions where the lender provides funding and the interest rate. These findings suggest that the fraction of regions where the lender operates is a more informative criterion rather than knowing the lender is geographically undiversified or not in the determining the loan prices and interests. Hence, the results provide evidence that higher degree of geographical diversification is associated to a lower level of interest rates in the P2P lending market.

Table 4
Empirical results

VARIABLES	(1) *Loan Rate*	(2) *Loan Rate*	(3) *Loan Rate*	(4) *Loan Rate*	(5) *Loan Rate*
Same Region	0.0001*				0.0001**
	(0.000)				(0.000)
Geo Diversification		-0.0946***			-0.0857***
		(0.014)			(0.015)
Fraction Area			0.0366***		0.0298***
			(0.002)		(0.002)
Geo Volatility				0.3411***	
				(0.008)	
Term (ln)	0.0164***	0.0164***	0.0164***	0.0165***	0.0164***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Size	0.0021***	0.0021***	0.0021***	0.0021***	0.0021***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.0130***	0.1076***	0.0106***	0.0042***	0.0968***
	(0.000)	(0.014)	(0.000)	(0.000)	(0.015)
Observations	882,610	882,610	882,610	882,610	882,610
R-squared	0.334	0.334	0.334	0.338	0.335
Lender Region FEs	Yes	Yes	Yes	Yes	Yes
Borrower Region FEs	Yes	Yes	Yes	Yes	Yes
R^2	0.334	0.334	0.334	0.338	0.335
Adjusted R^2	0.334	0.334	0.334	0.338	0.334
F (22, 882587)	14343	14350	14353	14425	13207
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000
RMSE	0.0098	0.0098	0.0098	0.0098	0.0098

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Columns (3) and (4) provide similar explanations to the previous one, by suggesting that a higher level of activities concentration correlates positively with interest rates. Hence, both coefficients are significant at 1%. Whilst, in Column 5 we report a model with all measures of geographical diversification. As before, *Geo Diversification* and *Fraction Area* shows similar coefficients as in previous estimates by confirming the activity concentration and fraction of regions in which the lender operates are more informative criteria than *Same Region dummy*.

Moving onto the coefficient on *Term (ln)*, all five regressions show a positive impact on *Interest Rate* at 1%. This is coherent with the view that lenders charge a higher interest rate to compensate for the longer loan term of the contracts, while *Size* enters all our regressions with a positive sign indicating that an increase in the amount lent by the lender to any borrower is positively related to an increase in the interest rate.

To summarize our results, we can confirm *H1* according to which in online peer-to-peer market, the lenders who geographically diversify their investments, can practice lower interest rates.

7. Robustness checks

Thus far, I use OLS regressions to test my hypotheses on the effect of geographical diversification on loan interest rates. However, potential outliers may bias my estimates. I could have two options. On the one hand, I could drop the outlier observations and re-run my estimates, but I would lose some information contained in them. On the other hand, I could use an estimator belonging to the family of GLS estimator called Robust Regression (Li, 2011), which provides more efficient estimates when outliers are present in the data. This method is based on the notion of Cook's distance that is extremely useful to identify data which can negatively affect the estimation. Then, outliers receive a potential weight in the regression framework based on the value of the Cook's Distance (for instance if the test shows a value larger than 1).

Table 5 reports the robustness tests. In general, the results reiterate those one presented in Table 4. Along the same lines as before, I find that the coefficient on *Term (ln)* is statistically and economically significant in all the regressions.

Table 5
Robustness checks

Variables	(1) *Loan Rate*	(2) *Loan Rate*	(3) *Loan Rate*	(4) *Loan Rate*	(5) *Loan Rate*
Same Region	0.0000				0.0000
	(0.000)				(0.000)
Geo Diversification		-0.3155***			-0.3145***
		(0.002)			(0.002)
Fraction Area			0.0067***		0.0064***
			(0.001)		(0.001)
Geo Volatility				0.0561***	
				(0.003)	
Term (ln)	0.0152***	0.0152***	0.0152***	0.0152***	0.0152***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Size	0.0007***	0.0007***	0.0007***	0.0007***	0.0007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.0169***	0.3324***	0.0165***	0.0154***	0.3310***
	(0.000)	(0.002)	(0.000)	(0.000)	(0.002)
Observations	882,610	882,610	882,610	882,610	882,610
Lender Region FEs	Yes	Yes	Yes	Yes	Yes
Borrower Region FEs	Yes	Yes	Yes	Yes	Yes
R^2	0.527	0.534	0.527	0.527	0.534
Adjusted R^2	0.527	0.534	0.527	0.527	0.534
F (22, 882587)	42800	43973	42779	42692	40459
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000
RMSE	0.00566	0.00566	0.00566	0.00567	0.00566

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Moving onto the variable of interest, I find that *Same Region* is not statistically significant, while Column (2) shows that on average an increase of the fraction of regions in the UK in which the lender operates reduces sensitively the level of interest rates by around 32 basis point and this effect is statistical significant. This result is another proof suggesting that fraction of regions in which the lender operates is a more informative criterion rather than the simple belonging to a same region rather another one in the determining the loan prices and interests. Lastly, *Fraction Area* and *Geo Volatility* positively affect the dependent variable, as seen in Table 4.

Even though the most significant coefficient estimates in Table 4 and 5 are referred respectively to *Fraction Area* and *Geo Volatility*, the most important factor affecting online peer-to-peer lending interest rates is *Geo Diversification*. Along the same line as before, we run a model with all the geographical diversification variables. Similarly, the coefficients on *Geo Diversification* and *Fraction Area* confirm previous results (Column 5). In relation to the control variables, the results re-iterate the same results reported in Table 4.

Unsurprisingly, R^2 is higher in the Robust Regression (Li, 2011) than OLS regressions. This entails this model explains more effectively the variance of the dependent variable.

Hence, the empirical results underline that more geographically diversified lenders charge lower interest rates, while less diversified lenders impose higher prices in the P2P transactions. Therefore, I can conclude that I find further support to *H1*, according to which the geographical diversification is related to a decrease in the loan interest rates.

8. Conclusions

This analysis is the first attempt to investigate the impact of the geographical diversification on the interest rate charged by lenders in the peer-to-peer lending market. While other studies investigate the role of the diversification in other contexts, such as the banking sector (among others, Deng and Elyasiani, 2008; Gulamhussen et al., 2012), there is no evidence currently about the effects of geographical diversification of the lenders (from a lender point of view) on the interest rates in the peer-to-peer markets (or platforms).

Exploiting a unique dataset based on 882,610 P2P transactions in a UK platform, Open Data Institute, I demonstrate that the geographical diversification of lenders is an important determinant of the loan interest rates in the peer-to-peer lending markets and platforms. Particularly, I find that geographical diversification is negatively related to the loan interest rates after controlling for loan terms, amount, and other borrower-, lender-specific factors. This evidence might be in line with the view that the diversification strategies reduce the risk through lower interest rates.

Overall, these findings contribute to the fast-growing strand of the literature that focuses on the importance of peer-to-peer lending markets, as an alternative source of financing for borrowers (Wei and Lin, 2017) compared to the traditional source represented by the banking activities (Duarte et al., 2012; Iyer et al., 2016; Claessens et al., 2018).

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